

BLUE WATERS

BREAKING THROUGH THE LIMITS

Optimizing Sparse Data Structures for Matrix-Vector Multiply

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GREAT LAKES CONSORTIUM
FOR PETASCALE COMPUTING



Summary

- Algorithms and Data Structures need to take memory prefetch hardware into account
- This talk shows one example - Matrix-vector multiply
- As we'll show, the results can be dramatic
- Prefetch is designed to improve realized memory bandwidth. How important is that?

BG/L Node

- Consider the simple case of memory copy:
 - Do $i=1, n$
 $a(i) = b(i)$
 - Suppose system memory bandwidth is 5.5GB/s. How fast will this loop execute?

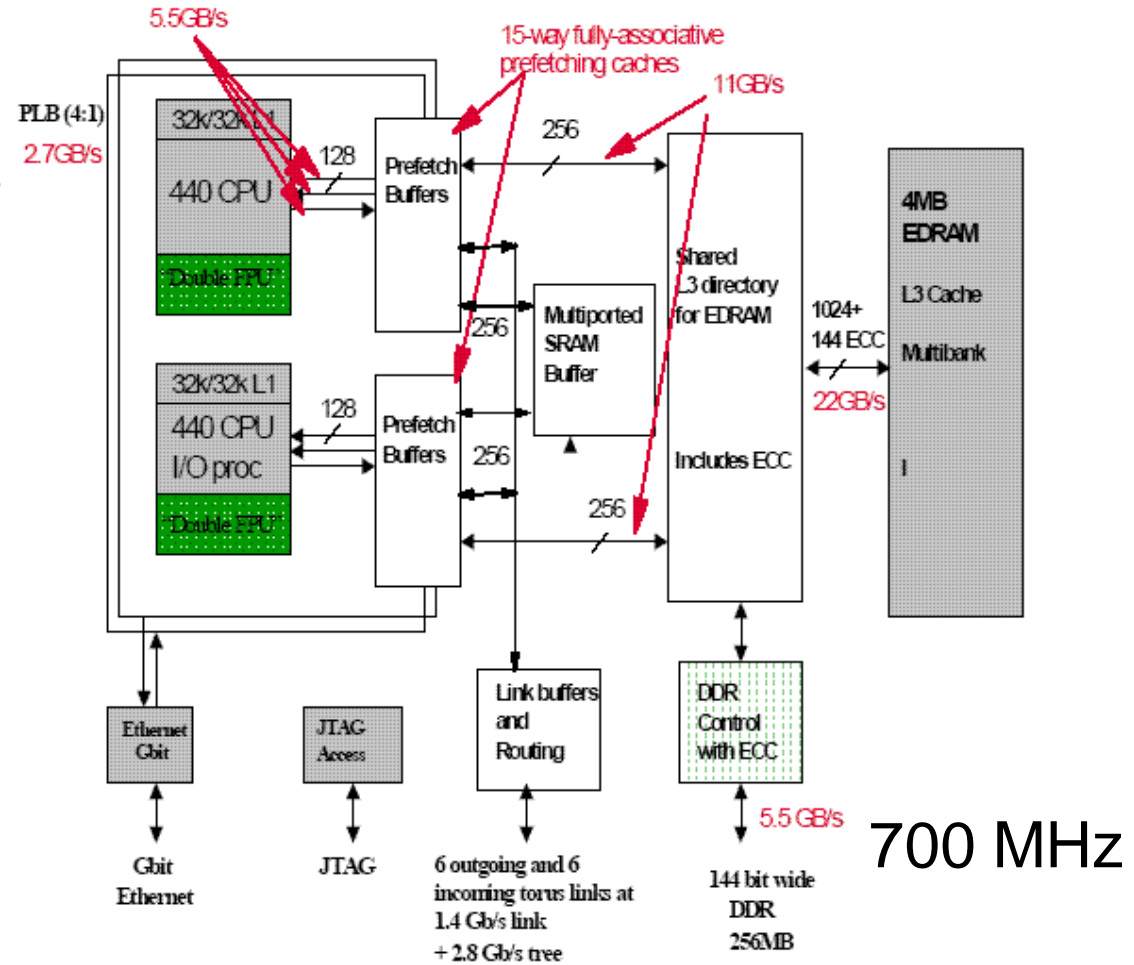


Figure 4: BlueGene/L Node Diagram. The bandwidths listed are targets.

Stream Performance Estimate

- Easy estimate: $11 \text{ GB/s} = 2 * 5.5 \text{ GB/Sec}$ to L3, 5.5 GB/Sec to main memory
 - Minimum link speed is 5.5 GB/s each way, Stream adds both
- Measured performance is 1.2 GB/s !
 - Why?
- Time to move each cache line
 - $5.5 \text{ GB/s} \sim 8 \text{ bytes/cycle}$ (memory bus bandwidth)
 - ~ 60 cycles L2 miss (latency)
 - $64 \text{ byte cache line} = 8 \text{ cycles (bandwidth)} + 60 \text{ cycles (latency)} = 68 \text{ cycles}$ or $\sim 0.94 \text{ byte/cycle}$ (read)
 - Stream bytes read + bytes written / time, so stream estimate is $2 * 0.94 \text{ byte/cycle}$, or 1.3 GB/sec
- This is typical (if anything, better than many systems because L2 miss cost is low)
- (there's more to this analysis, of course)

Example: Sparse Matrix-Vector Product

- Common operation for optimal (in floating-point operations) solution of linear systems
- Sample code (in C):

```
for row=1,n
    m  = i[row] - i[row-1];
    sum = 0;
    for k=1,m
        sum += *a++ * x[*j++];
    y[i] = sum;
```
- Data structures are $a[nnz]$, $j[nnz]$, $i[n]$, $x[n]$, $y[n]$

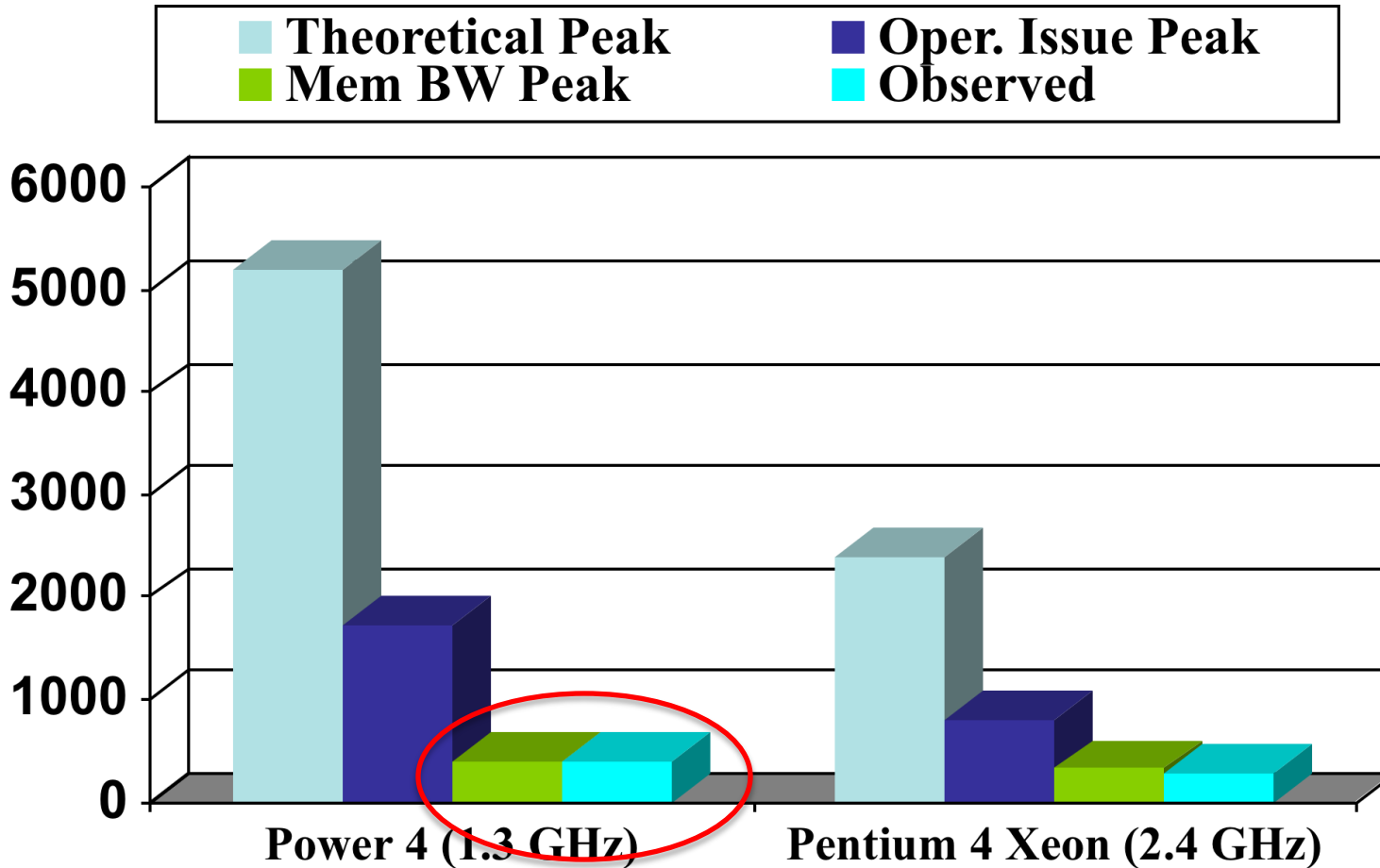
Simple Performance Analysis

- Memory motion:
 - $nnz (\text{sizeof}(\text{double}) + \text{sizeof}(\text{int})) + n (2 * \text{sizeof}(\text{double}) + \text{sizeof}(\text{int}))$
 - Assume a perfect cache (never load same data twice; only compulsory loads)
- Computation
 - nnz multiply-add (MA)
- Roughly 12 bytes per MA
- Typical WS node can move 1-4 bytes/MA
 - Maximum performance is 8-33% of peak

Realistic Measures of Peak Performance

Sparse Matrix Vector Product

One vector, matrix size, $m = 90,708$, nonzero entries $nz = 5,047,120$



Thanks to Dinesh Kaushik;
ORNL and ANL for compute time

Comments

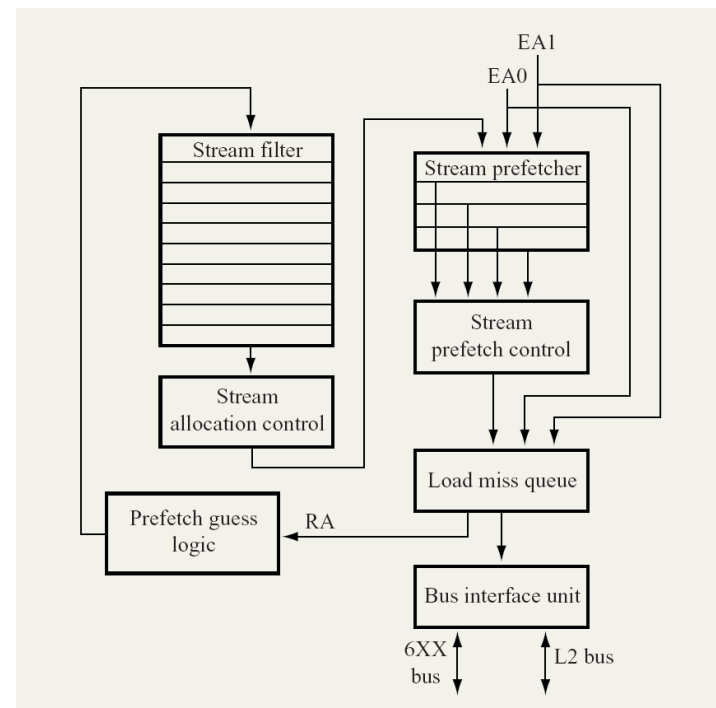
- Simple model based on memory performance gives good bounds on performance
 - Detailed prediction requires much more work; often not necessary or relevant to the algorithm designer
- Note that a key feature of the model is the use of *measured sustained memory bandwidth*
 - In many cases, achieved performance is close to that limit; advanced techniques, such as auto-tuners, cannot significantly boost performance
- But the measured memory bandwidth is low relative to the raw hardware bandwidth...

Prefetch Engine on IBM Power Microprocessors

- Beginning with the Power 3 chip, IBM provided a hardware component called a prefetch engine to monitor cache misses, guess the data pattern (“data stream”) and prefetch data in anticipation of their use.
- Power 4, 5 and 6 microchips enhanced this functionality.

	Data Streams	L2 Cache (MB)	L3 Cache(MB)
Power 4	8	~1.5	32
Power 5	8	1.875	36
Power 6	16	4	32

Data Stream and Cache Information



The Prefetch Engine on Power3 chip

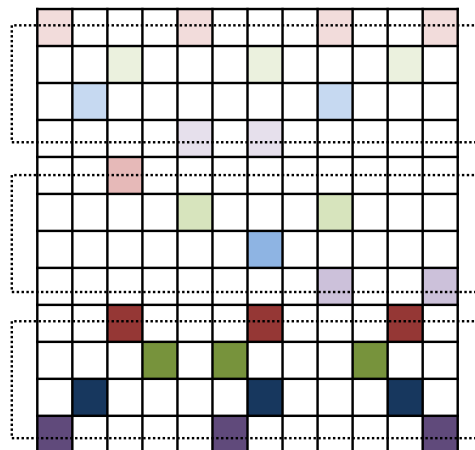
Inefficiency of CSR and BCSR formats

- The traditional CSR and Blocked CSR are hard to reorganize for data streams (esp > 2 streams) to enable prefetch, since the number of non-zero elements or blocks for every row may be different.
- Blocked CSR (BCSR) format can improve performance for some sparse matrices that are locally dense, even if a few zeros are added to the matrix.
 - If the matrix is too sparse (or structure requires too many added zeros), BCSR can hurt performance

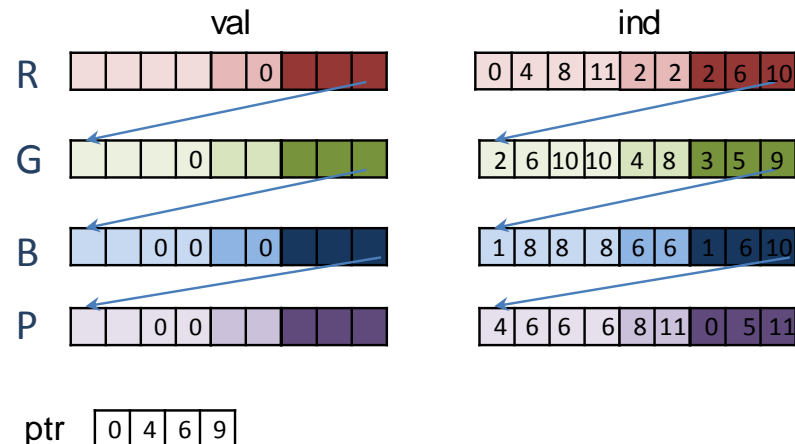
Streamed Compressed Sparse Row (S-CSR) format

- S-CSR format partitions the sparse matrix into blocks along rows with size of bs . Zeros are added in to keep the number of elements the same in each row of a block. The column indices for ZEROs in each row are set to the index of the last non-zero element in the row. The first rows of all blocks are stored first, then second, third ... and bs -th rows.
- For the sample matrix in the following Figure, $NNZ = 29$. Using a block size of $bs = 4$, it generates four equal length streams R, G, B and P. This new design only adds 7 zeros every 4 rows.

A sparse matrix ($N = 12$, $NNZ = 29$)



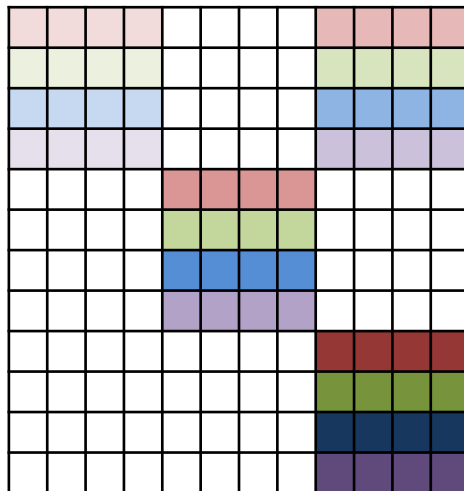
Streamed Compressed Sparse Row format (S-CSR)



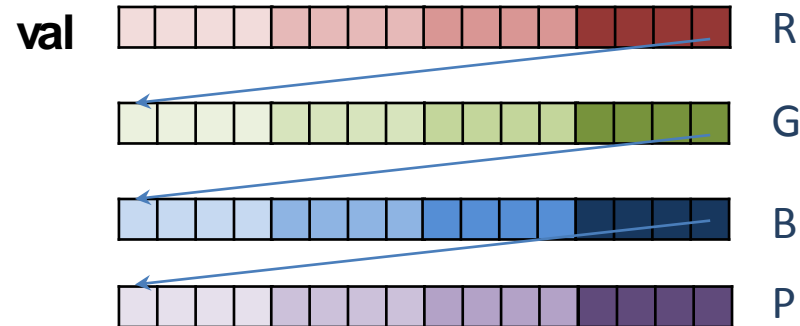
Streamed Blocked Compressed Sparse Row (S-BCSR) format

- When the matrix is locally dense and can be blocked efficiently with a few ZEROS added in, we can restore the blocked matrix using the similar idea as S-CSR format. The first rows of all blocks are stored first, then second, third ... and last rows. Using 4x4 block for example, it will generate R, G, B and P four equal length streams. We call this the Streamed Blocked Compressed Row storage format (S-BCSR).

A sparse matrix with 4X4 blocks



Streamed Blocked Compressed Sparse Row format (S-BCSR)



ind

0	2	1	2
---	---	---	---

ptr

0	2	3	4
---	---	---	---

Codes for CSR and S-CSR-2 formats

CSR	S-CSR-2	
<pre>void CSR(double *v, double *x, double *z, int *ii, int *idx, int NROW) { int i, j, n, *idxp; double sum1, *v1, xb; #pragma omp parallel for \ private(i,j,n, sum1,v1,idxp,xb) \ schedule(static) for (i=0; i<NROW; i++) { sum1 = 0.0; n = ii[i] - ii[0]; v1 = v+n; idxp = idx+n; for (j=ii[i]; j<ii[i+1]; j++) { xb = *(x + (*idxp++)); sum1 += (*v1++)*xb; } z[i] = sum1; } }</pre>	<pre>void S_CSR_2(double *v, double *x, double *z, int *ii, int *idx, int NROW) { int rbs = 2; int MROW =NROW/rbs, rrows = NROW%rbs, rslast = rbs; if(rrows > 0) {MROW++; rslast = rrows;} double *v1, *v2; int *ix1, *ix2; int i, j, k, nl, nm, ilen; double sum1, sum2; ilen = ii[MROW] - ii[0]; ix1 = idx; v1 = v; ix2 = ix1+ilen; v2 = v1+ilen; int MNR = MROW-1; if(rrows == 0) MNR = MROW; double *v10, *v20; int *iix1, *iix2;</pre>	<pre>#pragma omp parallel for \ private(i,j,nm, sum1,sum2,v10,v20,iix1,iix2) \ schedule(static) for (i=0; i<MNR; i++) { sum1 = sum2 = 0.0; nm = ii[i] - ii[0]; // two streams v10 = v1 + nm; v20 = v2 + nm; iix1 = ix1 + nm; iix2 = ix2 + nm; for (j=ii[i]; j<ii[i+1]; j++){ sum1 += *(v10++)*x[*iix1++]; sum2 += *(v20++)*x[*iix2++]; }//j z[rbs*i] = sum1; z[rbs*i+1] = sum2; } //i i = MNR; if (rrows == 1) { sum1 = 0.0; nm = ii[i] - ii[0]; v10 = v1 + nm; iix1 = ix1 + nm; for (j=ii[i]; j<ii[i+1]; j++) sum1 += *(v10++) * x[*iix1++]; z[rbs*i] = sum1; } }</pre>

Codes for BCSR-4 and S-BCSR-4 formats

BCSR-4

```
void BCSR_4(double *v, double *x, double *z, int *ii, int *idx, int MROW)
{
    int i, j, n, *idxp;
    double x1,x2,x3,x4,x5, sum1,sum2,sum3,sum4,sum5;
    double *xb, *v0;

#pragma omp parallel for \
    private(i, j, n, sum1, sum2, sum3, sum4, v0, xb, idxp) \
    schedule(static)
    for (i=0; i<MROW; i++) {
        n = ii[i] - ii[0];
        v0 = v+16*n;
        idxp = idx+n;
        sum1 = sum2 = sum3 = sum4 = 0.0;
        for (j=ii[i]; j<ii[i+1]; j++) {
            xb = x + 4*( *idxp++);
            x1 = xb[0]; x2 = xb[1]; x3 = xb[2]; x4 = xb[3];
            sum1 += v0[ 0] *x1 + v0[ 1] *x2 + v0[ 2] *x3 + v0[ 3] *x4;
            sum2 += v0[ 4] *x1 + v0[ 5] *x2 + v0[ 6] *x3 + v0[ 7] *x4;
            sum3 += v0[ 8] *x1 + v0[ 9] *x2 + v0[10] *x3 + v0[11] *x4;
            sum4 += v0[12] *x1 + v0[13] *x2 + v0[14] *x3 + v0[15] *x4;
            v0 += 16;
        }
        z[4*i ] = sum1;    z[4*i+1] = sum2;
        z[4*i+2] = sum3;  z[4*i+3] = sum4;
    }
}
```

S-BCSR-4

```
void S_BCSR_4(double *v, double *x, double *z, int *ii, int *idx, int MROW)
{
    int i, j, n, len, *idxp;
    double x1,x2,x3,x4,x5, sum1,sum2,sum3,sum4;
    double *xb, *v0, *v1, *v2, *v3, *v4, *v10, *v20, *v30, *v40;

    len = (ii[MROW] - ii[0])*4;
    v1 = v; v2 = v+len; v3 = v+len*2; v4 = v+len*3;

#pragma omp parallel for \
    private(i,j,n,sum1,sum2,sum3,sum4,v10,v20,v30,v40,xb,idxp) \
    schedule(static)
    for (i=0; i<MROW; i++) {
        n = ii[i] - ii[0];
        v10 = v1+4*n; v20 = v2+4*n;
        v30 = v3+4*n; v40 = v4+4*n;
        idxp = idx+n;

        sum1 = sum2 = sum3 = sum4 = 0.0;
        for (j=ii[i]; j<ii[i+1]; j++) {
            xb = x + 4*( *idxp++);
            x1 = xb[0]; x2 = xb[1]; x3 = xb[2]; x4 = xb[3];
            sum1 += v10[0]*x1 + v10[1]*x2 + v10[2]*x3 + v10[3]*x4;
            sum2 += v20[0]*x1 + v20[1]*x2 + v20[2]*x3 + v20[3]*x4;
            sum3 += v30[0]*x1 + v30[1]*x2 + v30[2]*x3 + v30[3]*x4;
            sum4 += v40[0]*x1 + v40[1]*x2 + v40[2]*x3 + v40[3]*x4;
            v10 += 4; v20 += 4; v30 += 4; v40 += 4;
        }
        z[4*i ] = sum1;    z[4*i+1] = sum2;
        z[4*i+2] = sum3;  z[4*i+3] = sum4;
    }
}
```

Some Sparse Matrices used in the tests

- We used matrices from the University of Florida collection

- All the codes were compiled with “xlc_r -O3 -qstrict -q64 -qtune=auto -qarch=auto”. 64KB page size was set for text and data on Power5 and Power6 chips.

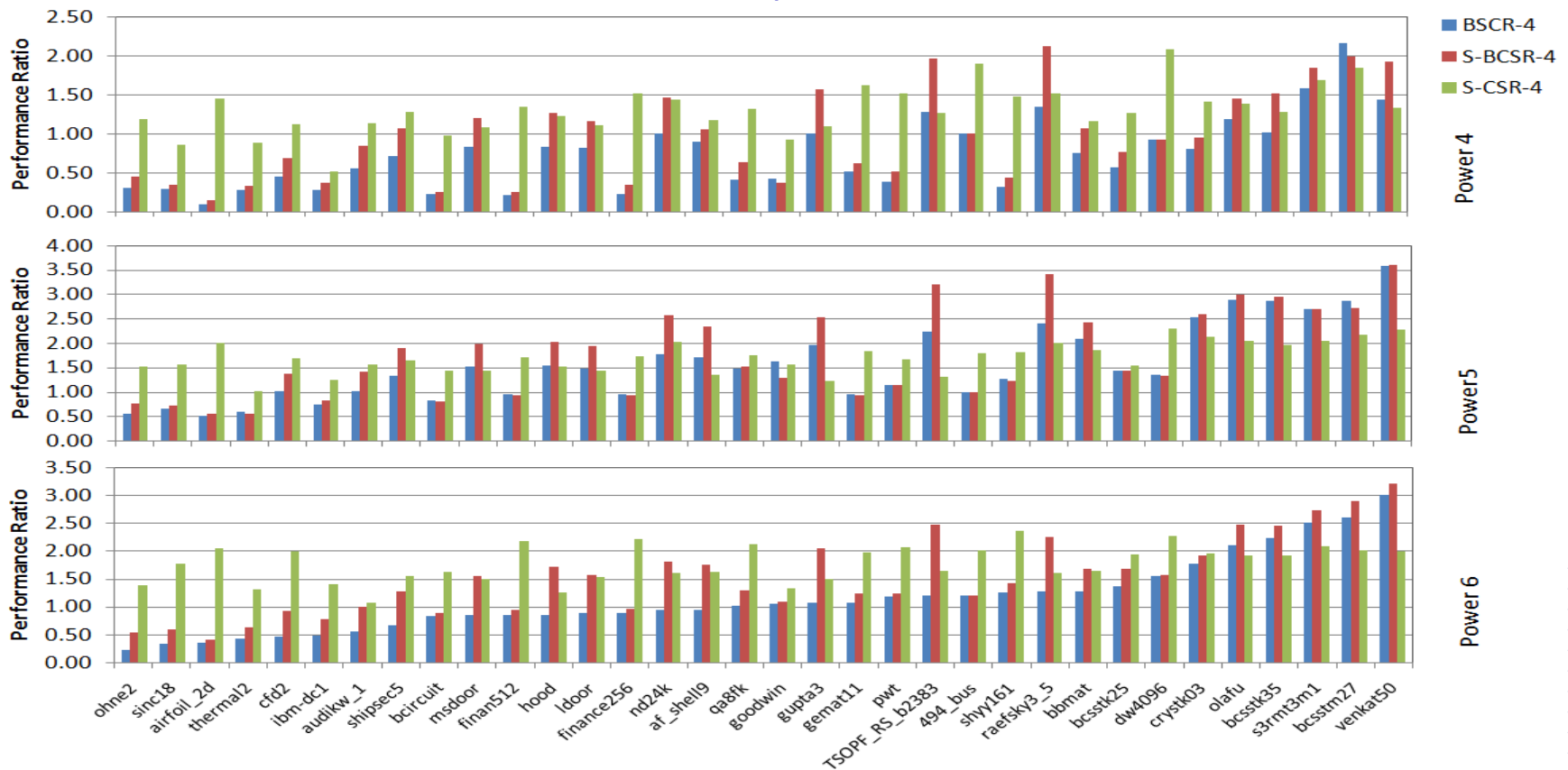
- Performance measured is that average of three runs after a “cold start” run

Matrix	N	NNZ	Matrix	N	NNZ
494_bus	494	1080	bcsstm27	1224	28,675
shipsec5	179860	5146478	gemat11	4929	33,185
airfoil_2d	14214	259688	bai-dw4096	8192	41,746
ibm-dc1	116835	766396	bcsstk35	30237	740,200
gupta3	16783	4670105	crystk03	24696	887,937
Hood	22054	5494489	goodwin	7320	324,784
msdoor	415863	10328399	bcircuit	68902	375,558
Ldoor	952203	23737339	shyy161	76480	329,762
bcsstk25	15439	133840	bbmat	38744	1,771,722
finan512	74752	335872	olafu	16146	515,651
qa8fk	66127	863353	venkat50	62424	1,717,792
nd24k	72000	14393817	pwt	36519	181,313
af_shell9	504855	9046865	sinc18	16428	973,826
audikw_1	943695	39297771	ohne2	181343	11,063,545
cf2	123440	1605669	thermal2	1228045	4,904,179
raefsky3_5	106000	7443840	TSOPF_RS_b2383	38120	16,171,169
finance256	37376	167936	s3rmt3m1	5489	112,505

Performance Ratio compared to CSR format

- S-CSR format is better than CSR format for all (on Power 5 and 6) or Most (on Power 4) matrices
- S-BCSR format is better than BCSR format for all (on Power 6) or Most (on Power 4 and 5) matrices
- Blocked format performance from ½ to 3x CSR.

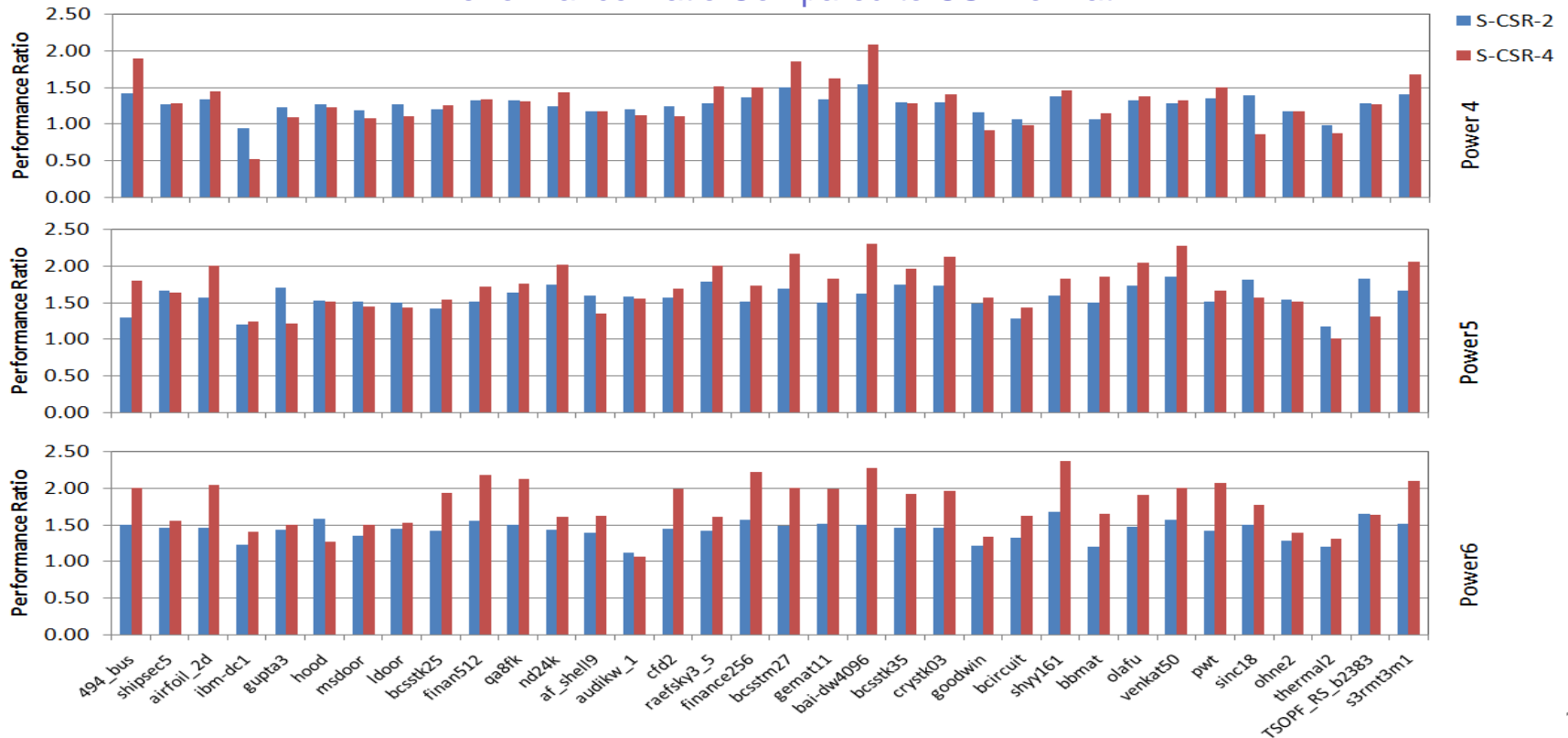
Performance Ratio Compared to CSR format



S-CSR formats with two and four streams

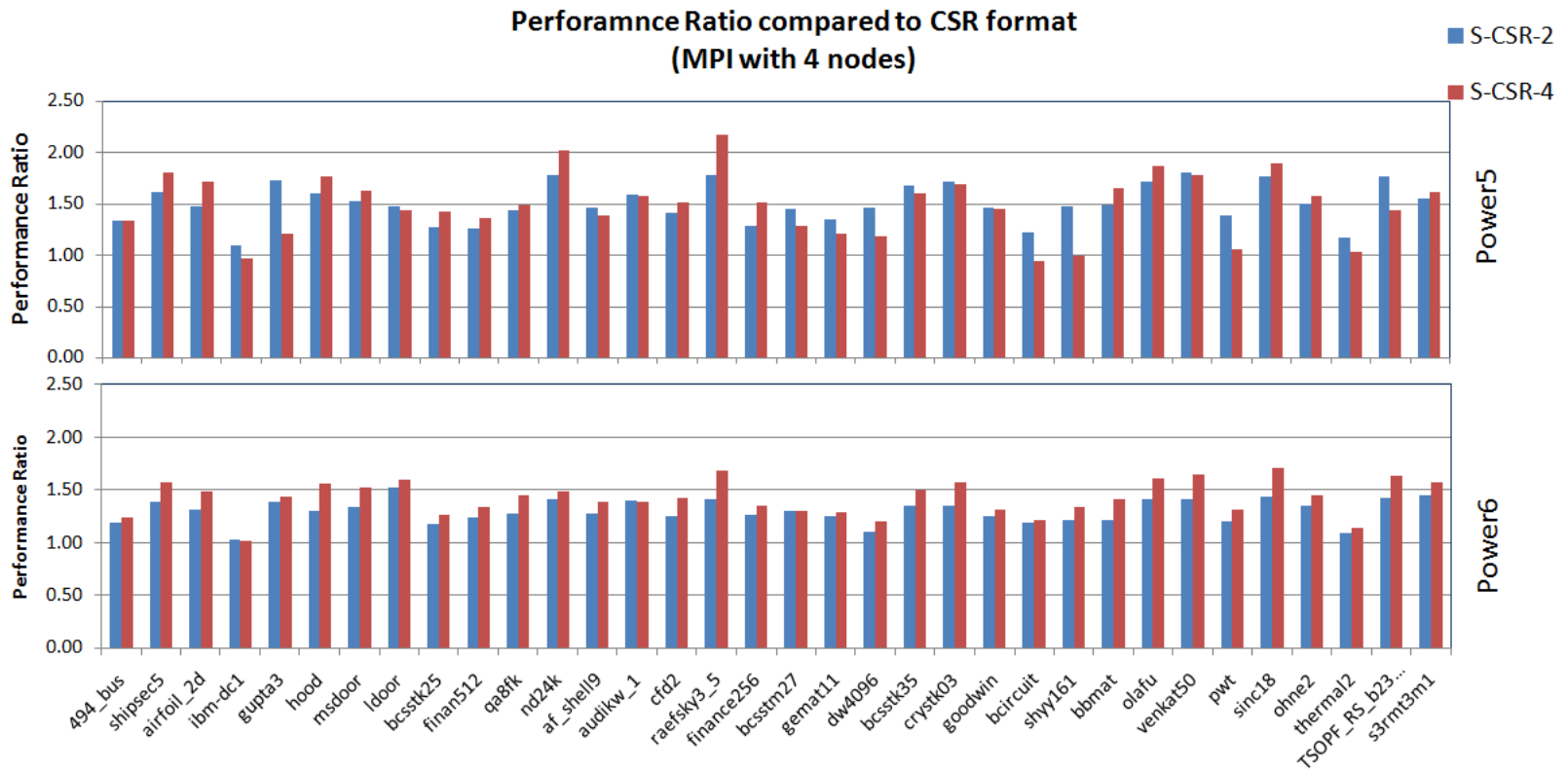
- S-BCSR-4 is generally better than S-BCSR-2 on Power 6.
- On Power 4 and 5, these two are mixed.
- S-CSR-4 format can achieve over 2x performance improvement of CSR.

Performance Ratio Compared to CSR format



MPI with 4 nodes

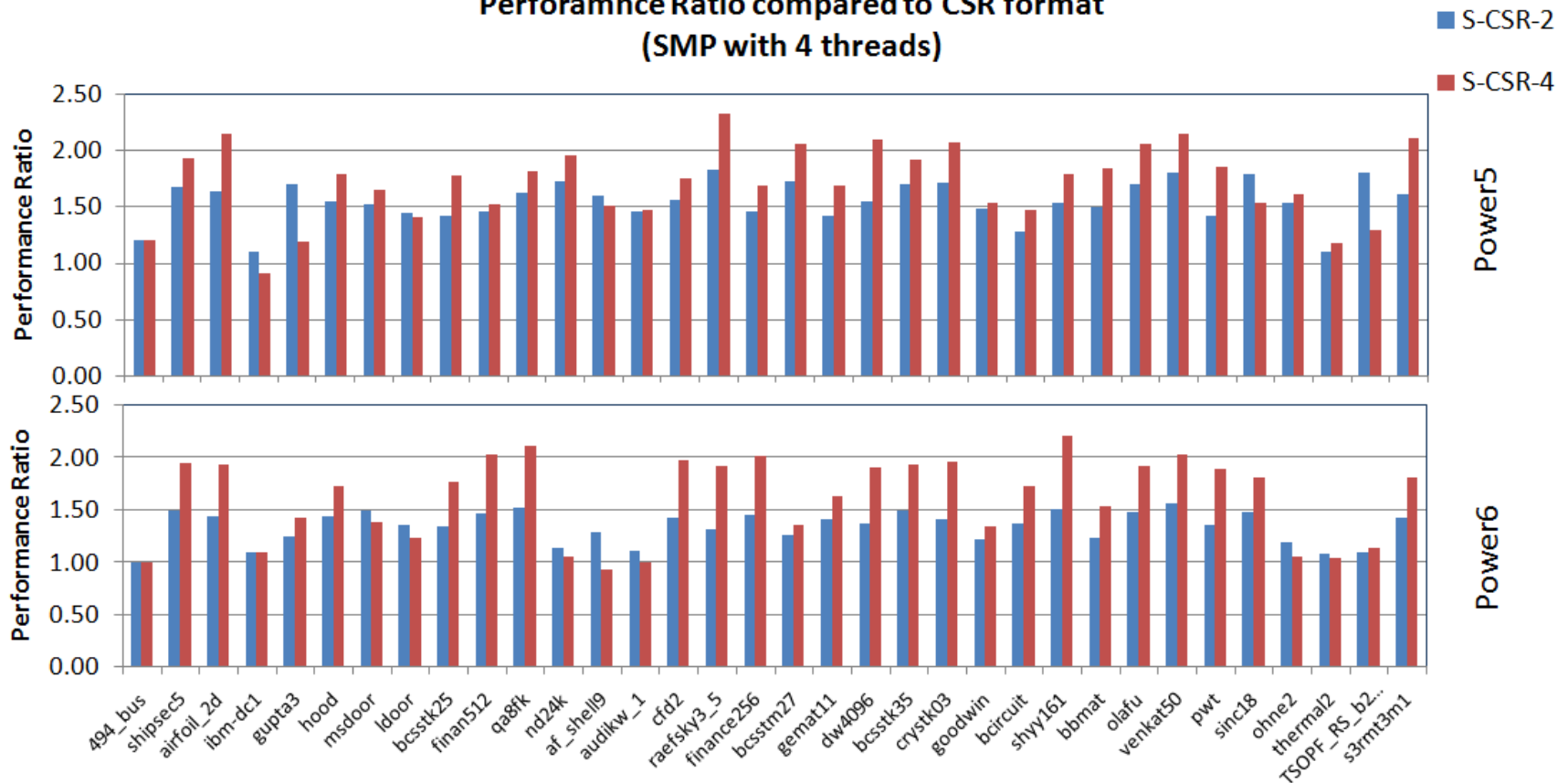
- Parallel tests with MPI using 4 nodes on P5 and P6. At most 50% improvement achieved.
- Probably due to communication overhead (these are small matrices)



SMP with 4 threads

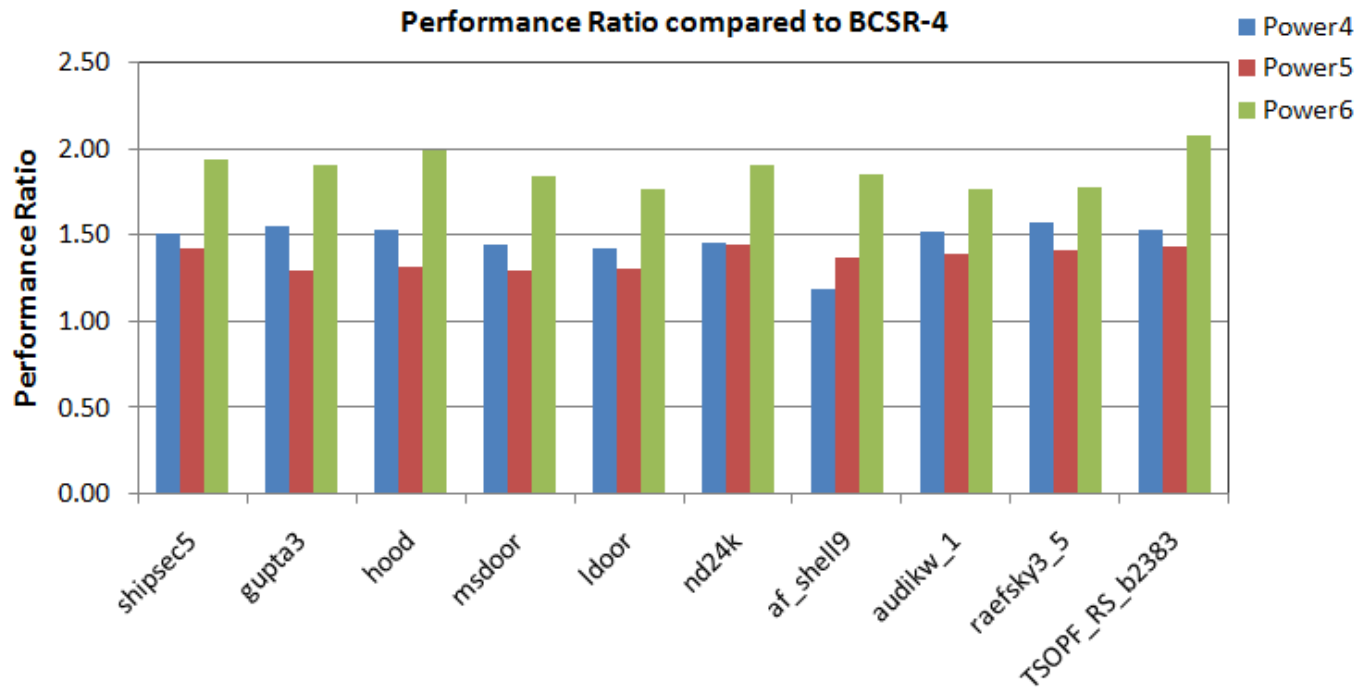
- SMP with 4 threads also tested on P5 and P6. Typical performance boost of 1.5-2x over CSR
- Shows prefetch works with multiple threads (more tests needed)

Performance Ratio compared to CSR format
(SMP with 4 threads)



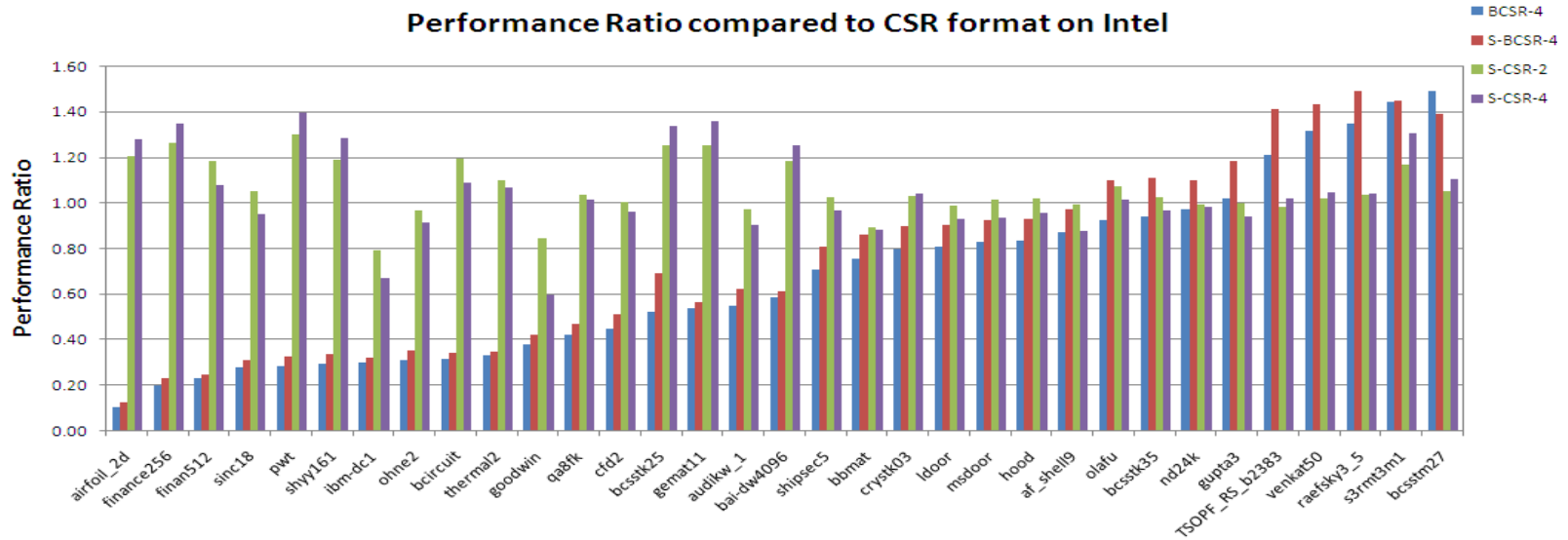
Comparison of S-BCSR-4 format to BCSR-4 format

- The matrices are chosen with large data size (> 32 MB) *and* the performance of BCSR format is close to *or* better than CSR format.
- Performance Improvement of S-BCSR-4 format compared to BCSR-4 format:
P4: 20 -60%, P5: 30 -45%, P6: 75 -108%



Streamed format on Intel processors

- The tests were also run on `abe.ncsa.uiuc.edu` (Xeon/Clovertown, 2.33 GHz, 2x4 MB L2 cache)
- S-CSR-2 and/or S-CSR-4 format can result in better performance than CSR format for many matrices.
- S-BCSR-4 format is better than BCSR-4 format for all the matrices except for “`bcsstm27`”, which is small and fits in cache. For most matrices, S-BCSR format provides a 10 - 20% of performance improvement.



Summary and Future Work

- The streamed CSR and BCSR storage formats can significantly improve the performance of SpMV for a variety of matrices on IBM processors. Over 100% performance improvement can be achieved.
 - Simulation results for POWER7 also are good
- The new formats also show the benefits on Intel processors.
- We will compare the new format with other auto-tuning packages, such as Berkeley-OSKI, and with other approaches to improve performance within rows (such as sorted CSR)
 - New formats will be provided within PETSc
 - Initial results: S-CSR provides more performance than OSKI
- Alignment and SIMD instructions will also be considered in the new formats.
- Perhaps most important – extension to other matrix-vector operations used in preconditioners